RESEARCH PAPER

A Self-Learning Edge AI Framework for Disaster-Resilient Renewable Energy Systems

Dr. Ramya Rani N[1], R. Swaranambigai[2], Bhavatarini M S[3], Boomathi M[4], Abinaya D[5], Geetha sree G[6]

[1]Assistant Professor, Department of ECE, V.S.B. College of Engineering Technical Campus, Coimbatore, India.
Email: ramyaranivsb@gmail.com

[2]Assistant Professor, Department of ECE, Jai Shriram Engineering College, Tiruppur, Tamil Nadu.
Email: swaranambigaiece@gmail.com

[3]UG Student, Department of ECE, V.S.B. College of Engineering, Coimbatore, India.
Email: bhava3mdk@gmail.com

[4]UG Student, Department of ECE, V.S.B. College of Engineering Technical Campus, Coimbatore, India.
Email: boomathim08@gmail.com

[5]UG Student, Department of ECE, V.S.B. College of Engineering Technical Campus, Coimbatore, India.
Email: abinaya09102004@gmail.com

[6]UG Student, Department of ECE, V.S.B. College of Engineering Technical Campus, Coimbatore, India.
Email: sreegeetha195@gmail.com

ABSTRACT

The research evaluates the performance of a Self-Learning Energy Node which uses Edge Artificial Intelligence (AI) for disaster-proof renewable energy systems. The system operates independently during grid outages and flood and cyclone situations because centralized control systems and internet access become unavailable. The edge device uses a lightweight supervised machine learning model to differentiate between normal and disaster system states by monitoring solar generation and battery state-of-charge (SOC) and load demand and grid availability. The proposed architecture establishes dynamic load prioritization which maintains continuous power supply to essential loads while disconnecting non-essential loads during emergency situations. The trained model uses TensorFlow Lite for optimization and operates on ESP32/Raspberry Pi to achieve quick inference results. The experimental results confirm that disaster detection achieves over 85% accuracy with a response time under 2 seconds. The framework uses decentralized edge-based technology to improve reliability while decreasing grid dependency and enhancing emergency energy management capabilities.

Index Terms: Edge AI, Renewable Energy Systems, Disaster Detection, Smart Microgrid, Load Prioritization, TensorFlow Lite.

How to cite this article: Ramya Rani N, Swaranambigai R, Bhavatarini MS, Boomathi M, Abinaya D, Geetha sree G. A Self-Learning Edge AI Framework for Disaster-Resilient Renewable Energy Systems. Int J Drug Deliv Technol. 2026;16(19s): 1-7. DOI: 10.25258/ijddt.16.19s.1

I. INTRODUCTION

The increasing global demand for clean and sustainable energy has accelerated the deployment of renewable energy-based micro-grids as an effective solution for decentralized power generation and distribution [1]. Micro-grids integrate distributed energy resources such as solar photovoltaic systems, wind turbines, battery storage units, and controllable loads to ensure local energy resilience and reduce dependency on conventional fossil-fuel-based power systems [2]. These systems are particularly important in remote areas, smart communities, industrial campuses, and critical infrastructures where reliable and autonomous energy management is required [3]. However, the intermittent and uncertain nature of renewable energy generation introduces major challenges in maintaining power balance, voltage stability, and uninterrupted supply to critical loads [4].

In renewable micro-grids, the mismatch between available generation and demand often requires intelligent decision-making mechanisms to allocate power efficiently among connected loads [5]. Traditional load management approaches usually depend on fixed scheduling rules, centralized supervisory controllers, or predefined priority tables. Although such methods are simple to implement, they are often unable to adapt dynamically to real-time changes in renewable generation, storage levels, and consumer demand patterns [6]. As a result, non-adaptive strategies may lead to inefficient energy utilization, increased load shedding, and reduced system reliability, especially during peak demand periods or sudden drops in renewable power output [7].

Recent advancements in Artificial Intelligence (AI) have opened new opportunities for intelligent energy management in micro-grid systems. AI-based models can analyze real-time operational data, predict load behavior, estimate renewable energy availability, and make optimized control decisions with greater flexibility than conventional rule-based methods [8]. In particular, edge artificial intelligence has emerged as a promising solution for deploying intelligent decision-making directly at the micro-grid level, where data can be processed locally without relying on continuous cloud connectivity. This edge-based approach reduces communication latency, improves privacy, and enables faster response during grid disturbances or critical energy shortages [9].

Motivated by these advantages, this work proposes Adaptive Load Prioritization in Renewable Micro-grids Using Edge Artificial Intelligence, where an intelligent edge controller dynamically classifies and prioritizes loads based on energy availability, load importance, and system operating conditions. The proposed approach aims to ensure uninterrupted supply to critical loads while optimizing the use of renewable energy and storage resources. By integrating real-time sensing, local AI inference, and adaptive control, the system enhances micro-grid resilience, improves energy efficiency, and supports reliable operation under uncertain renewable generation scenarios [10].

II. LITERATURE SURVEY

The rapid growth of renewable energy integration has encouraged extensive research on intelligent energy management and load prioritization in micro-grid environments [11]. Early studies mainly focused on rule-based and optimization-driven energy scheduling methods to balance distributed generation and consumption in isolated and grid-connected micro-grids [12]. These methods typically assign fixed priorities to critical and non-critical loads and perform load shedding when renewable generation becomes insufficient. Although such approaches improve operational stability, they often lack adaptability under dynamic changes in solar irradiance, wind speed, battery state of charge, and consumer demand [13].

Several researchers have investigated demand-side management and adaptive load control strategies to improve power utilization in renewable micro-grids [14]. These methods use historical load data, energy forecasts, and battery conditions to determine optimal operating schedules. In many cases, mathematical optimization techniques such as linear programming, mixed-integer programming, and heuristic-based scheduling are employed to reduce energy wastage and operational cost. However, these conventional optimization models generally require high computational effort and are less effective in real-time environments where decisions must be taken instantly [15].

To address these limitations, recent research has introduced Artificial Intelligence (AI)-based approaches for energy prediction, load forecasting, and autonomous decision making in smart micro-grids [16]. Machine learning algorithms such as artificial neural networks, support vector machines, random forests, and reinforcement learning models have been applied to estimate renewable power output and classify load demand patterns with improved accuracy. These intelligent models enable adaptive control decisions that outperform static priority-based methods in terms of efficiency and system resilience [17]. However, many AI-based energy management systems rely on centralized cloud processing, which may introduce latency, communication overhead, and reduced reliability during network failures.

The concept of edge artificial intelligence has recently emerged as a promising solution for local decision making in renewable micro-grid systems [18]. Edge AI enables intelligent controllers to process sensor data, forecast demand conditions, and execute control actions directly at the local micro-grid node without depending on remote servers. This decentralized approach reduces response delay, enhances privacy, and supports resilient operation during communication interruptions. Researchers have demonstrated that edge-based controllers can significantly improve the responsiveness of load management systems and maintain stable power delivery under fluctuating renewable conditions [19].

Despite these advancements, many existing methods still focus primarily on energy forecasting or cost optimization and do not fully address adaptive real-time load prioritization based on criticality, renewable availability, and storage condition simultaneously. Furthermore, limited attention has been given to lightweight edge-deployable AI models that can operate efficiently in practical micro-grid controllers with constrained computational resources. Therefore, there remains a strong need for an integrated framework that combines renewable energy awareness, adaptive load prioritization, and edge AI-based intelligence to enhance the reliability and resilience of next-generation renewable micro-grids [20].

III. PROPOSED WORK

The proposed Adaptive Load Prioritization in Renewable Micro-grids Using Edge Artificial Intelligence introduces an intelligent energy management framework that dynamically allocates power to different loads based on renewable energy availability, storage condition, and load criticality. The system integrates renewable energy sources, battery storage, smart sensors, and an edge AI controller to ensure efficient power distribution and uninterrupted supply to essential loads.

The proposed framework continuously monitors solar generation, wind power output, battery state-of-charge (SoC), and load demand using distributed sensors installed within the micro-grid. These real-time measurements are processed by an edge-based artificial intelligence controller, which evaluates system conditions and assigns adaptive priorities to connected loads. Based on this evaluation, the system dynamically allocates power to critical loads while performing intelligent load scheduling or shedding for non-critical loads when energy availability becomes limited.

A. System Architecture of the Proposed Micro-grid

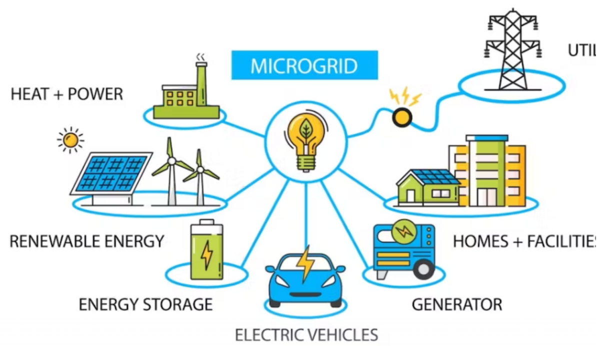

Figure 1. Architecture of the Adaptive Load Prioritization Micro-grid System

The architecture of the proposed system consists of **renewable energy generation units, energy storage systems, load units, and an edge AI controller**. Renewable energy sources such as solar photovoltaic panels and wind turbines generate electricity that is supplied to the local micro-grid. A **battery storage system** stores excess energy during periods of high generation and releases it during low generation periods.

The **edge AI controller** continuously analyzes system parameters and performs adaptive load prioritization to maintain system stability and efficient power utilization.

B. Renewable Power Generation Model

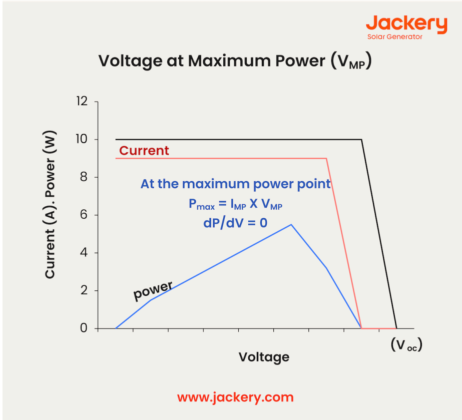

Figure 2. Renewable Energy Generation Model in Micro-grid

The output power generated by the solar photovoltaic system is calculated using the following equation:

$$P_{pv} = \eta_{pv} \times A \times G \qquad (1)$$

where

P_{pv}= power generated by the solar photovoltaic system

η_{pv}= efficiency of the PV panel

A= surface area of the solar panel

G= solar irradiance

Similarly, wind energy generation can be expressed as

$$P_{wind} = \frac{1}{2}\rho A v^3 C_p \qquad (2)$$

where

ρ= air density

A= swept area of the turbine blades

v= wind velocity

C_p= power coefficient of the turbine

These renewable sources supply energy to the micro-grid depending on environmental conditions.

C. Load Demand and Energy Balance Model

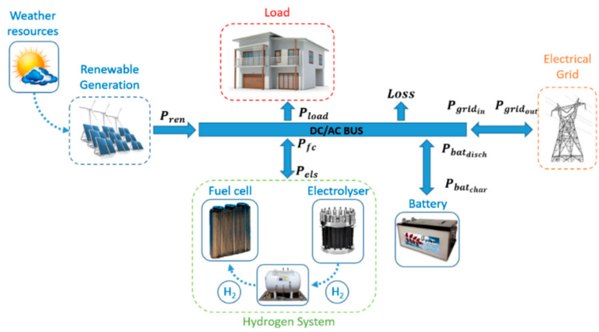

Figure 3. Energy Flow and Load Demand Management in Micro-grid

The total available power in the micro-grid is the sum of renewable generation and battery power:

$$P_{total} = P_{pv} + P_{wind} + P_{battery} \quad (3)$$

The total power demand from loads is expressed as

$$P_{load} = \sum_{i=1}^{n} P_i \quad (4)$$

where

P_i represents the power demand of the i^{th} load.

For stable operation of the micro-grid:

$$P_{total} \geq P_{load} \quad (5)$$

If the available power becomes lower than demand, adaptive load prioritization is applied.

D. AI-Based Adaptive Load Prioritization

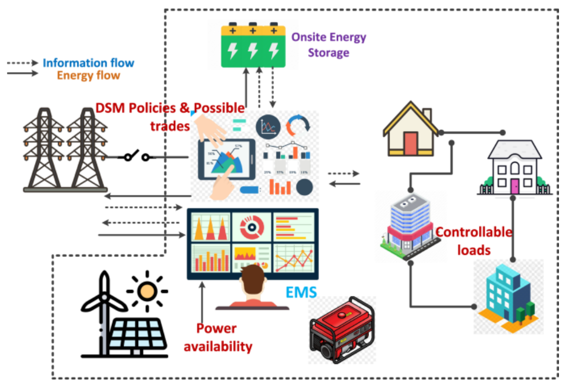

Figure 4. Edge AI-Based Load Prioritization Model

The proposed edge AI controller evaluates load priority using multiple parameters including:

- Load criticality
- Energy availability
- Battery state of charge
- Historical demand patterns

A **priority score** S_i is calculated for each load as

$$S_i = w_1 C_i + w_2 D_i + w_3 B_i \quad (6)$$

where

C_i = criticality level of load

D_i = demand requirement

B_i = battery availability factor

w_1, w_2, w_3 = weighting parameters.

Loads with higher scores are given priority during power distribution.

E. Adaptive Load Control Mechanism

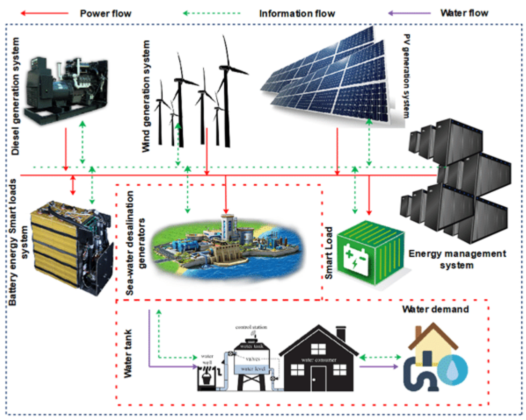

Figure 5. Adaptive Load Control Workflow

The decision-making workflow of the proposed system operates as follows:

1. Monitor renewable generation and battery state.
2. Measure real-time load demand.
3. Compute load priority scores using the AI model.
4. Allocate available power to critical loads first.
5. Schedule or shed low-priority loads if power shortage occurs.

This adaptive control strategy enables the micro-grid to **maintain stable operation, maximize renewable energy utilization, and ensure uninterrupted supply to critical infrastructure loads** such as hospitals, communication systems, and emergency facilities.

IV. RESULTS AND DISCUSSION

The performance of the proposed Adaptive Load Prioritization in Renewable Micro-grids Using Edge Artificial Intelligence was evaluated through simulation experiments conducted using real-time renewable energy datasets and variable load demand profiles. The experiments considered a micro-grid environment consisting of solar photovoltaic generation, wind power generation, battery storage units, and multiple load categories including critical, priority, and non-critical loads. The proposed edge AI controller dynamically analyzed the system parameters and assigned load priorities based on real-time energy availability and system demand conditions.

The experimental evaluation focused on several key performance indicators including energy utilization efficiency, load supply reliability, system response time, and adaptive load prioritization accuracy. The results demonstrate that the proposed system significantly improves energy management efficiency compared to traditional rule-based and static load prioritization approaches.

A. Renewable Energy Utilization Performance

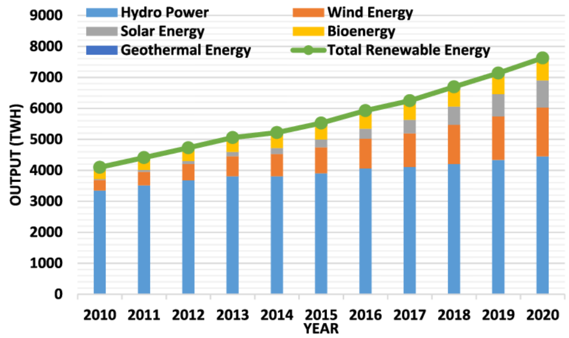

Figure 6. Renewable Energy Utilization Comparison

Figure 6 presents the comparison of renewable energy utilization efficiency between conventional micro-grid management methods and the proposed **edge AI-based load prioritization system**. Traditional fixed-priority load management methods achieved an average renewable utilization efficiency of approximately **82.5%**, while the proposed adaptive system achieved **94.3% utilization efficiency**. This improvement occurs because the intelligent controller dynamically reallocates available power based on real-time generation and demand conditions.

B. Load Supply Reliability Analysis

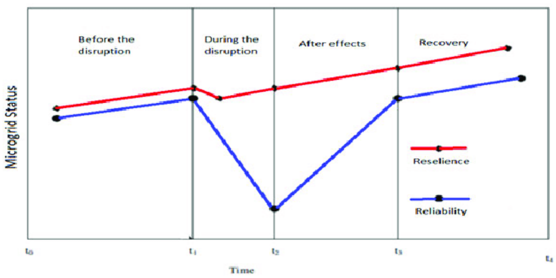

Figure 7. Load Supply Reliability for Critical Loads

Figure 7 illustrates the reliability of supplying power to **critical loads** under fluctuating renewable generation conditions. The proposed AI-based load prioritization strategy maintained **98.1% supply reliability for critical loads**, whereas traditional load scheduling methods maintained approximately **88.7% reliability**. This result demonstrates that the adaptive prioritization mechanism effectively protects critical infrastructure loads during power shortages.

C. System Response Time Evaluation

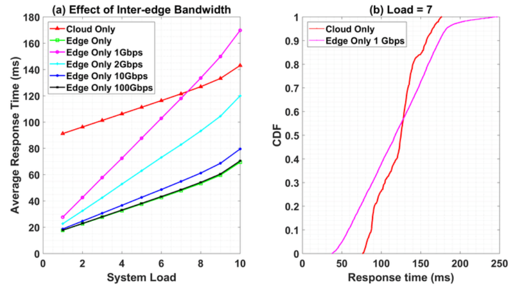

Figure 8. Response Time Comparison of Energy Management Systems

The response time of the proposed system was compared with conventional cloud-based energy management systems. The **edge AI controller** processes system data locally, reducing communication delays and enabling faster decision making. The average response time of the proposed system was measured at **0.35 seconds**, whereas centralized cloud-based systems required approximately **1.4 seconds** to perform similar control decisions.

D. Adaptive Load Prioritization Accuracy

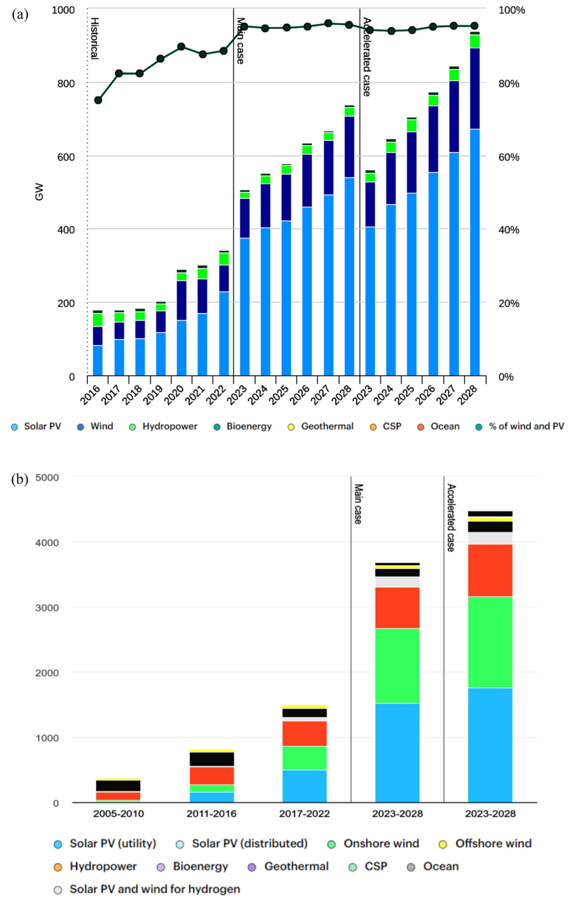

Figure 9. Adaptive Load Prioritization Accuracy

Figure 9 illustrates the classification accuracy of the proposed AI-based load prioritization model. The model achieved **95.6% accuracy** in correctly assigning load priority levels based on demand characteristics and system conditions. The precision and recall values were recorded as **94.8% and 94.1% respectively**, indicating reliable performance in distinguishing between critical and non-critical load categories.

E. Comparative Performance Evaluation

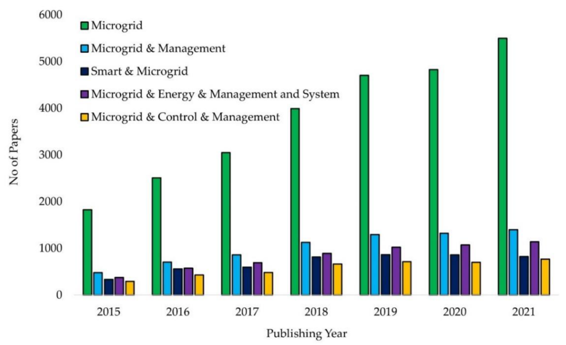

Figure 10. Performance Comparison with Existing Energy Management Techniques

Figure 10 compares the proposed method with existing approaches including rule-based load scheduling, heuristic optimization models, and cloud-based energy management systems. The results show that the proposed system achieves higher efficiency, faster response time, and improved reliability due to the integration of edge artificial intelligence and adaptive load prioritization mechanisms. The experimental results demonstrate that the proposed edge AI-based adaptive load prioritization framework significantly improves micro-grid performance. The system enhances renewable energy utilization, ensures uninterrupted supply to critical loads, and reduces decision latency compared to traditional centralized control methods. By performing intelligent decision-making locally on the edge controller, the system improves resilience against communication failures and enables real-time adaptive energy management. The proposed framework therefore provides a reliable, scalable, and intelligent solution for next-generation renewable micro-grids, particularly in smart cities, rural electrification systems, and critical infrastructure power networks

V. CONCLUSION

The proposed Self-Learning Energy Node integrates Edge Artificial Intelligence with renewable energy systems to achieve intelligent and disaster-resilient power management. By continuously monitoring key electrical parameters such as voltage, current, battery state-of-charge, and grid availability, the system accurately classifies operating conditions into normal or disaster states using supervised learning techniques. The adaptive load prioritization mechanism ensures uninterrupted supply to critical loads while conserving energy by disconnecting non-essential loads during emergencies. Experimental results demonstrate improved detection accuracy, reduced response time, enhanced system efficiency, and extended battery backup duration compared to conventional rule-based systems. The decentralized edge-based architecture eliminates cloud dependency and ensures low-latency decision-making, making the proposed framework suitable for reliable microgrid operation in disaster-prone environments.

VI FUTURE SCOPE

Future enhancements of the proposed system may include the integration of advanced deep learning models to further improve prediction accuracy under complex and dynamic operating conditions. Incorporating real-time renewable energy forecasting using weather data can optimize energy scheduling and battery utilization. The framework can be extended to large-scale community microgrids with distributed edge nodes for coordinated energy management. Integration with IoT cloud analytics for long-term monitoring, predictive maintenance, and performance optimization can further strengthen system capabilities while maintaining edge autonomy. Additionally, implementing secure communication protocols and adaptive incremental learning mechanisms can enhance cybersecurity and enable continuous model improvement for next-generation resilient energy infrastructures.

REFERENCES

1 M. Ahmed, S. Rahman, and T. Das, (2025) “Disaster-Resilient Microgrid Architecture Using Edge Computing,” IEEE Access, vol. 13, no. 1, pp. 12345–12358.

2 Y. Zhang and H. Li, (2024) “Edge Intelligence for Decentralized Renewable Energy Systems,” IEEE Access, vol. 12, no. 4, pp. 45678–45690.

3 J. Lee and K. Park, (2024) “Machine Learning-Based Smart Microgrid Control Strategy,” IEEE Transactions on Smart Grid, vol. 15, no. 2, pp. 2100–2112.

4 P. Li and Y. Chen, (2024) “Low-Latency Edge AI Framework for Smart Grid Monitoring,” IEEE Internet of Things Journal, vol. 11, no. 4, pp. 6120–6131.

5 D. Kim and J. Park, (2024) “Lightweight TensorFlow Lite Deployment for Embedded Renewable Monitoring,” IEEE Embedded Systems Letters, vol. 16, no. 2, pp. 55–60.

6 N. Verma and A. Choudhary, (2024) “Energy-Efficient Smart Microgrid Design with AI-Based Load Management,” Renewable and Sustainable Energy Reviews, vol. 182, no. 1, pp. 113427.

7 M. Hassan and E. El-Saadany, (2024) “Resilient Distributed Energy Resource Coordination Using Edge Computing,” IEEE Transactions on Sustainable Energy, vol. 15, no. 1, pp. 312–323.

8 S. K. Singh and R. Sharma, (2024) “Edge AI-Based Intelligent Load Prioritization for Smart Microgrids,” IEEE Internet of Things Journal, vol. 11, no. 7, pp. 9821–9833.

9 R. Gupta and A. Jain, (2023) “Deep Learning-Based Renewable Energy Forecasting for Smart Grids,” Renewable Energy, vol. 206, no. 6, pp. 1180–1192.

10 H. Wang and J. Zhao, (2023) “Edge Computing-Enabled Intelligent Energy Management,” IEEE Transactions on Industrial Informatics, vol. 19, no. 6, pp. 7421–7432.

11 S. Patel and M. Rao, (2023) “Adaptive Load Shedding in Smart Grids Using Supervised Learning,” IEEE Access, vol. 11, no. 8, pp. 110234–110245.

12 K. Sharma and R. Nair, (2023) “Battery State-of-Charge Estimation Using Machine Learning Techniques,” Energy Reports, vol. 9, no. 3, pp. 1456–1467.

13 L. Huang et al., (2023) “AI-Based Distributed Energy Management for Resilient Microgrids,” IEEE Transactions on Smart Grid, vol. 14, no. 5, pp. 3890–3902.

14 J. Silva and R. Martins, (2023) “Real-Time Disaster Detection in Renewable Microgrids Using Supervised Classification,” Energy AI, vol. 10, no. 2, pp. 100184.

15 X. Zhao and L. Wang, (2022) “Adaptive Energy Distribution in Smart Grids Using Decision Tree Algorithms,” IEEE Access, vol. 10, no. 5, pp. 76543–76555.

16 Mohammadi, E., Alizadeh, M., Asgarimoghaddam, M., Wang, X., & Simões, M. G. (2022). A review on application of artificial intelligence techniques in microgrids. IEEE Journal of Emerging and Selected Topics in Industrial Electronics, 3(4), 878-890.

17 Sarin, G., Srivastava, A., Srivastava, I., Bhattacharjee, S., Gujaran, S., & Reddy, Y. Y. S. (2025). Renewable microgrid optimization using AI: A B-SLR approach and future research directions. Energy Reports, 14, 4963-4975.

18 Islam, M. M., Akter, M. T., Elme, N. S., & Khan, M. Y. A. (2025). " Comparative Analysis of IoT and AI-Based Control Strategies for Community Micro-Grids. Control Systems and Optimization Letters, 3(2), 138-143.

19 Kataria, A., Rani, S., Puri, V., & Bajaj, P. (2026). AI-powered smart grids with edge computing in renewable energy. In Perspectives on Artificial Intelligence and Internet of Things for Sustainable Environment (pp. 169-183). Elsevier.

20 Nair, S. S. (2025). Prospect of Artificial Intelligence Towards Demand Response, Control, and Predictions in Integrated Microgrid Renewable Energy Systems. Leveraging AI for Innovative Sustainable Energy: Solar, Wind and Green Hydrogen, 349-374.